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14. ABSTRACT
In this research effort, we supported the HMDS and AMDS programs run by NVESD. We performed basic research for processing GPR and EMI sensor data and for performing sensor fusion. Significant performance enhancements were made and technology transfer included algorithm code and feature descriptions.

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Enter List of papers submitted or published that acknowledge ARO support from the start of the project to the date of this printing. List the papers, including journal references, in the following categories:

(a) Papers published in peer-reviewed journals (N/A for none)

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(1) Ratto, C.R., Morton, K. D., Collins, L. M., and Torrione, P. A., “A Hidden Markov Context Model for GPR-Based Landmine Detection Incorporating Dirichlet Process Priors”, IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Vancouver, BC, pp. 874-877 , July 2011.

(2) Tantum. S. L., Morton, K.D. Jr., Torrione, P.A., Collins, L.M., “Frequency domain electromagnetic induction sensor data feature extraction and processing for improved landmine detection,” SPIE Defense and Security Symposium, April 2011.

(3) Torrione, P.A., Collins, L.M., “The Viterbi algorithm as an approach for incorporating spatial information into air/ground interface inference,” SPIE Defense and Security Symposium, April 2011.

(4) Ratto, C.R., Morton, K.D. Jr., Collins, L.M., Torrione, P.A., “Physics-based features for contextual factors affecting landmine detection with ground-penetrating radar,” SPIE Defense and Security Symposium, April 2011.

(5) Manandhar A., , Morton, K.D. Jr., Collins, L.M., Torrione, P.A., “Multiple instance learning for landmine detection using ground-penetrating radar data,” SPIE Defense and Security Symposium, April 2011.

(6) Ratto, C.R., Morton, K.D. Jr., Collins, L.M., Torrione, P.A., “Contextual learning in ground-penetrating radar data using Dirichlet process priors,” SPIE Defense and Security Symposium, April 2011.

(7) Torrione, P.A., Morton, K.D. Jr., Ratto, C.R., Gunter, M. and Collins, L.M., “Vehicle mounted video-based change detection for novel anomaly detection,” SPIE Defense and Security Symposium, April 2011.

(8) Wood, J.J., Bolton, J., Casella, G., Collins, L.M., Gader P., Glenn, T.C., Lee, W., Mueller, R., Smock, B., Torrione P.A., Wilson, J.N., “Comparison of algorithms for finding the air-ground interface in ground-penetrating radar signals,” SPIE Defense and Security Symposium, April 2011.

(9) Ratto, C., Torrione, P., Collins, L.M., "Estimation of Soil Permittivity Through Autoregressive Modeling of Time-Domain Ground-Penetrating Radar Data," 2010 IEEE International Conference on Wireless Information Technology and Systems, Honolulu, Hawaii, August 28-September 3, 2010.

(10) Ratto, C., Torrione, P., Collins, L., “Context-Dependent Landmine Detection with Ground-Penetrating Radar Using a Hidden Markov Context Model,” IEEE IGARSS, July 25, 2010.

(11) Torrione, P., Collins, L., “Spatial Latency Reduction in GPR Processing Using Stochastic Sampling,” IEEE IGARSS, July 25, 2010.

(12) Tantum, S. L., Torrione, P., Collins, L., “Sparse model representations of target signatures for improved landmine detection using frequency domain electromagnetic induction sensors,” SPIE Defense and Security Symposium, April 2010.

(13) Morton, K., Torrione, P., Collins, L., “Non-parametric Bayesian time-series modeling and clustering of time-domain ground penetrating radar landmine responses,” SPIE Defense and Security Symposium, April 2010.

(14) Ratto, C., Torrione, P., Collins, L.M., “Context-dependent feature selection using unsupervised contexts applied to GPR-based landmine detection,” SPIE Defense and Security Symposium, April 2010.

(15) Tantum, S. L., Torrione, P., Collins, L. M., “Fusion of ground-penetrating radar and electromagnetic induction sensors for landmine detection and discrimination,” SPIE Defense and Security Symposium, April 2010.

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(18) Fails, E. B., Torrione, P. A., and Collins, L. M., “Performance comparison of frequency domain quadrapole and dipole electromagnetic induction sensors in a landmine detection application,” 2008 International Symposium on Aerospace/Defense Sensing and Controls,

Orlando, Florida, March 2008, in press.

(19) Torrione, P. A. and Collins, L. M., "Application of Markov random fields to landmine detection in ground-penetrating radar data," 2008 International Symposium on Aerospace/Defense Sensing and Controls, Orlando, Florida, March 2008, in press.

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Number of Non Peer-Reviewed Conference Proceeding publications (other than abstracts):

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(d) Manuscripts

Received Paper

TOTAL:

Number of Manuscripts:

Books

Received Paper

TOTAL:

Patents Submitted

Patents Awarded

Awards

Graduate Students

NAME	PERCENT_SUPPORTED	Discipline
Peter Torrione	1.00	
Kenneth Morton	1.00	
Christopher Ratto	1.00	
FTE Equivalent:	**3.00**	
Total Number:	**3**	

Names of Post Doctorates

NAME	PERCENT_SUPPORTED
Peter Torrione	1.00
Kenneth Morton	1.00
Li Tang	1.00
Stacy Tantum	0.30
FTE Equivalent:	**3.30**
Total Number:	**4**

Names of Faculty Supported

NAME	PERCENT_SUPPORTED	National Academy Member
Leslie Collins	0.10	
Peter Torrione	1.00	
FTE Equivalent:	**1.10**	
Total Number:	**2**	

Names of Under Graduate students supported

NAME	PERCENT_SUPPORTED
FTE Equivalent:	
Total Number:	

Student Metrics

This section only applies to graduating undergraduates supported by this agreement in this reporting period

The number of undergraduates funded by this agreement who graduated during this period: 0.00

The number of undergraduates funded by this agreement who graduated during this period with a degree in science, mathematics, engineering, or technology fields:...... 0.00

The number of undergraduates funded by your agreement who graduated during this period and will continue to pursue a graduate or Ph.D. degree in science, mathematics, engineering, or technology fields:...... 0.00

Number of graduating undergraduates who achieved a 3.5 GPA to 4.0 (4.0 max scale):...... 0.00

Number of graduating undergraduates funded by a DoD funded Center of Excellence grant for Education, Research and Engineering:...... 0.00

The number of undergraduates funded by your agreement who graduated during this period and intend to work for the Department of Defense 0.00

The number of undergraduates funded by your agreement who graduated during this period and will receive scholarships or fellowships for further studies in science, mathematics, engineering or technology fields:...... 0.00

Names of Personnel receiving masters degrees

<u>NAME</u>

Total Number:

Names of personnel receiving PHDs

<u>NAME</u>
Peter Torrione
New Entry

Total Number: **2**

Names of other research staff

NAME	PERCENT_SUPPORTED
FTE Equivalent:	
Total Number:	

Sub Contractors (DD882)

Inventions (DD882)

Scientific Progress

See attachment

Technology Transfer

Statement of the problem studied

The primary focus of this work is on developing robust algorithms and algorithm fusion architectures to reduce false alarm rates and improve detection rates for landmines. Two major systems were studied, the AMDS system and the GSTAMIDS/HMDS GPR. In the EMI-based systems, false alarm reductions were achieved algorithmically, and in the multi-sensor systems additional false alarm rate reduction was obtained when

Summary of the most important results

A list of the most important results is shown below, with relevant details following.

1. Robust pre-screener implemented for NIITEK radar, modified for theatre data
2. Improved ground-bounce tracking algorithms developed
3. Feature-based algorithms proposed and tested
4. Sensor and feature fusion algorithms proposed and tested
5. New context dependent algorithm developed
6. L3 data processing

LMS-Based Prescreener

The Wichmann/Niitek radar is a very wide band (200 MHz to 7 GHz) impulse radar with extremely low radar cross section. Thus, the radar implicitly solves many of the d problems previously associated with subsurface discrimination using ground penetrating radar based systems. Furthermore, due to the high bandwidth of this radar, accurate phenomenology of buried objects can often be discerned including some of their inner structure. This has lead us to hypothesize that sub-surface target identification and discrimination may be possible using the signals measured with this radar system. However target discrimination is often too computationally expensive to meet the real-time requirements of this, a vehicular system.

These real-time requirements have led us to develop a two stage algorithm which is divided into pre-screening and feature-processing stages. The goal of the pre-screening stage is to quickly flag potential locations of interest and to pass these locations along to the feature-processor. The feature processor will then attempt to separate targets from naturally occurring clutter and make final decisions regarding the confidence values for each of the alarms presented by the prescreener. Thus the amount of data which is analyzed by the feature processor is limited by the number of alarms the prescreener generates. Ideally, the splitting of data processing into two stages should allow for more complicated feature-based discrimination algorithms to operate on the small subset of pre-screener-flagged data in a real-time manner. In this paper, we present results from field and blind tests generated by both the pre-screener and the pre-screener followed by the feature-based processor.

A two-stage algorithm for landmine detection with a ground penetrating radar (GPR) system was developed and tested extensively under this effort. First, 3-D data sets are processed using a computationally inexpensive pre-screening algorithm which flags potential locations of interest. These flagged locations are then passed to a feature-based processer which further discriminates target-like anomalies from naturally occurring clutter. Current field trial (over 6500 square meters) and blind test results (over 39000 square meters) were obtained and these show at least an order of magnitude improvement over other radar system-based detection algorithms on the same test lanes. Results from the blind lanes, which are the most realistic test, are summarized below. Note that this algorithm has been implemented in the real system and is currently operating in the field.

For blind test lanes, data was collected by Niitek and burned to CDs for processing. Resulting alarm files were presented to the independent contractor within 24 hours of receiving the data. No modifications were made to these algorithms at any point during or between the two separate test data collections. The ground truth for the blind lanes is sequestered and known only to the government sponsor. Blind test lanes consist of buried (no surface) plastic and metal-cased anti-tank landmines. Algorithm scores on the blind lanes were generated by the independent contractor.

In the eastern US site, blind lane performance was comparable to the calibration lane performance. These scores were generated by the third party contractor and represent aggregate scores over several lanes spanning 14000 square meters. At this site, the pre-screener achieves a Pd of 90% at a false alarm rate of approximately 0.0002 false alarms per meter squared, and the feature-based processor achieves a Pd of 90% at approximately 0.0001 false alarms per meter squared. This performance represents an improvement of approximately two orders of magnitude over other fielded radar systems.

Pre-screener results from the western US site also coincide with results on those calibration lanes. These results represent aggregate scores over several lanes spanning 25000 square meeters. The pre-screener achieves a Pd of 90% at approximately 0.0001 false alarms per meter squared. The feature based processor was not run on this data due to insufficient training data. Again, this performance represents an improvement of approximately two orders of magnitude over other fielded radar systems.

Ground Bounce Tracking

In landmine detection applications, the goal is to localize all landmines with a minimum number of false alarms. This means that features that can distinguish the landmines from the background clutter have to be formulated and extracted. Historically, a combination of features from both the time-domain and the frequency domain are required to achieve low false alarm rates. One issue that has been a problem for landmine detection algorithms is eliminating the radar return from the ground, or the “ground bounce” (GB), as it is a significant source of false alarms. It is therefore generally accepted that the GB must be detected and removed.

Inaccurate location of the GB can also impact feature extraction. A number of algorithms have been proposed for GB tracking and clutter removal in order to increase the accuracy of landmine detection. Each of these approaches performed well in relatively benign conditions, but may encounter difficulties in more difficult scenarios. The main challenge for GB tracking in the real world is that there are a variety of ground conditions, such as soil, sandy, gravel, asphalt surfaces, or ground covered with vegetation. These various ground surfaces often result in significant anomalies unrelated to the presence of a landmine. These anomalies are inhomogeneous and the statistical properties of the GB responses may vary with position. GB response characteristics are also influenced by weather conditions, such as soil humidity, rain and snow.

Due to the dielectric discontinuities between the ground and the air, the main feature of the GB is a sharp peak in each A scan. As a simple GB tracking algorithm, GB locations can be roughly estimated by finding the maximum response along each of these A scans, which will be referred to as the "global maximum" method. In most cases, particularly in benign environments, the ground/air interface does in fact generate the maximum response in the GPR signal. However, there are a number of cases where the maximum response is generated by other factors, such as the interface between snow and the air or surface metallic objects and the air. Other subsurface anomalies can also be problematic for a simple GB tracker. These anomalies cause GB tracking based on a global maximum to "jump" from one location to another, which significantly impacts the accuracy of landmine detection, particularly if GPS interference occurs in the vicinity of a landmine.

An alternative yet still simple ground tracker is based on finding local maximum responses, which will be referred to as the "constrained maximum" method. For every DT/XT location, this algorithm searches for the maximum radar response in a "safe" neighborhood based on the previous GB estimate in the adjacent A Scan, where the size of the neighborhood is defined with a pre-defined window size. For a given data set, this parameter can be chosen so that both the accuracy and the efficiency of the GB tracking are optimized. However, if a variety of data sets are blended, it is difficult to choose this parameter so as to make it fit all experimental conditions, which degrades the overall performance. Another choice is to apply a Kalman filter based on the global maximum, which potentially provides a more accurate GB tracker than the simple approaches mentioned above. In essence, the Kalman filtering formulation is the minimum mean squared error (MMSE) estimate to the global maximum with a Gaussian observation noise, in which linear models are required.16 However, sometimes it is hard to relate the GB locations to the observations with linear functions due to the inhomogeneous GB signatures. As Sequential Monte Carlo sampling is a technique to estimate the state of nonlinear/non-Gaussian stochastic systems, it is potentially a better choice for GB tracking problems. During this project we implemented each of these approaches and considered their efficacy on a wide variety of field data.

Generally speaking, and averaged over a wide variety of data, it appeared that the best choice for stable robust ground tracking was the Kalman filter, although we are currently continuing to investigate other techniques. The constrained maximum and global maximum are computationally simple, but subject to fairly significant error. The Kalman filter is computationally more expensive, but provides better results both in terms of error (when the data has been manually ground truthed) and in terms of ROC performance. Several of the more advanced techniques considered provided marginally better performance, but required parameters to be set carefully and were considerably more computationally intense.

Context-dependent learning

It has been well-established over the years in collaborating on the GSTAMIDS, HMDS, and AMDS programs that the performance of feature-based pattern recognition algorithms for buried threat detection vary significantly with respect to environmental context. Context-dependent learning has therefore been proposed as a technique for improving overall performance by exploiting this property and applying context-specific algorithm fusion rules. To characterize the subsurface environment, we developed physics-based features that have been shown to be indicative of known soil properties in simulated scenarios and weather measurements in field-collected data. Consider the figures below; Figure 3 illustrates the results of identifying soil dielectric constant, conductivity, surface correlation length, and number of subsurface scatterers from simulated GPR data; Figure 4 illustrates the results of identifying dirt/gravel temperature and soil moisture content from field-collected GPR data. Results show that using the developed features and a relevance vector machine classifier has enabled excellent prediction of these environmental factors.

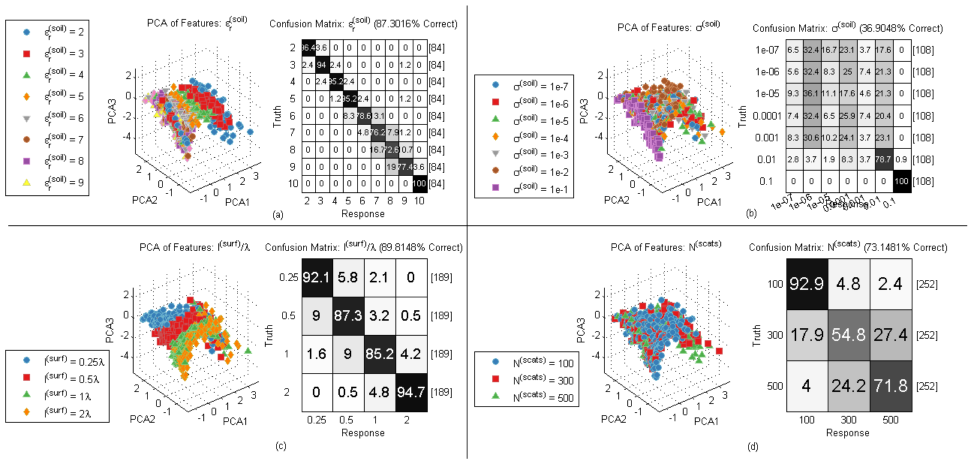

Figure 1. Identification of contextual factors in simulated GPR data.

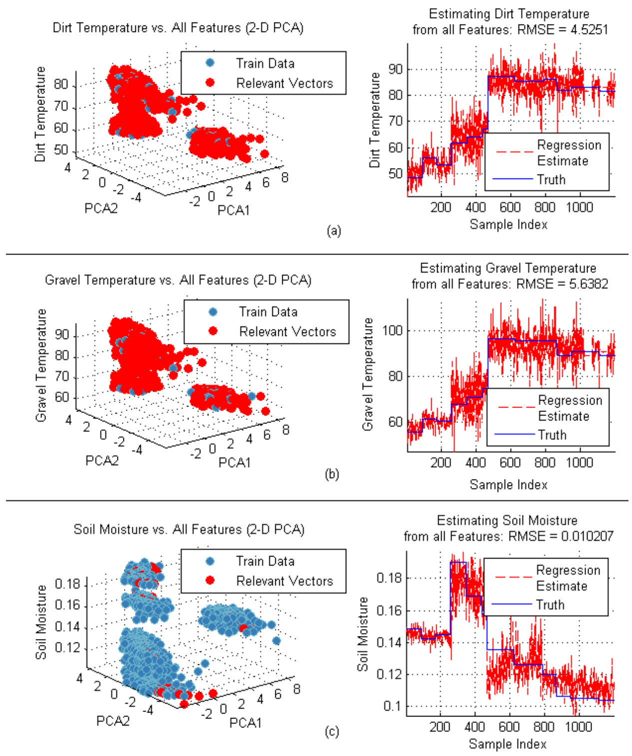

Figure 2. Identification of contextual factors in field-collected GPR data.

After these features have been extracted from raw GPR data, a statistical model is used to identify the unique contexts from which the data was collected. Current research has focused on scenarios where "contextual ground truth" is unavailable, and the number of contexts is uncertain. Nonparametric Bayesian models, such as infinite-order Gaussian mixtures (which assume independent observations) and hidden Markov models (which assume spatially-dependent observations) have been proposed for modeling the distribution of context in GPR data and variational learning has been employed to infer these models with minimal computational overhead. Figure 3 illustrates an example of a hidden Markov context model. The infinite-order HMM was used to automatically learn the number of contexts (which was effectively 4), and the results of context identification on a particular lane are shown here. On this lane, context appears to be tied to the presence of a strong subsurface layer.

Feature-based algorithms

We considered an technique called the texture feature coding method, based out of the biomedical image processing literature, that uses texture features to classify data. The texture feature coding method developed by Horng is a technique for translating intensity images to class-number images based on thresholded gradients taken along different orientations of an intensity image. For each pixel (i, j) in an image, we seek to generate a texture feature class number based on the 3pixel by 3pixel sub-image around (i, j). We considered directly implementing the 2-D approach as initially posed, but then considered several 3-D extensions to apply it to GPR data.

Off-lane GPR data provides a more stringent test of energy-based pre-screening anomaly detection algorithms. However, due to the low computational complexity of these algorithms, we can utilize feature-based processing at flagged locations of interest to improve PD/FAR performance. We have developed a 3-D extension to the 2-D texture feature coding method originally developed by Horng and used for target identification by Liang et al. In this work we apply 3-D TFCM to GPR responses taken from pre-screener flagged locations of interest. Several different features are then extracted from the resulting TFCM class numbers. Relevance vector machines trained on these features are then used to separate landmine feature sets from clutter feature sets. Current PD/FAR curves indicate significant performance improvements for RVM-based feature processing over energy-based pre-screening algorithms. Results also indicate improvements in target discrimination for 3-D TFCM features compared to their 2-D counterparts. Our future work in this area will include exploration of other TFCM features, other feature sets, and different learning machines for target/clutter classification.

Sensor/Feature Fusion

In collaboration with UFL, U Missouri, and U. Louisville we have shared features across a wide variety of data sets and developed algorithms for performing feature level fusion. To date, the algorithms developed at UFL have out-performed the algorithms we have tested.

AMDS Algorithm Development

The data processing stream for L3 GPR data has been under consideration. The L3 GPR system is a frequency-domain system, and so to transform the data to the more typical range- (temporal/spatial) domain, an inverse fast Fourier transform (IFFT) must be applied. Investigations have suggested that while there is some question as to the current implementation of the IFFT to obtain the range-domain GPR data, the differences between an ideal implementation and the current implementation do not substantially alter the range-domain data. It may be important to keep these differences in mind, however, as future revisions to the system could result in aberrations in the range-domain data if these differences become significant but are not considered. Continuing work will investigate the potential implications of the differences between the current frequency-domain data to range-domain signal IFFT transform in the remainder of the data processing stream (alarm generation and classification).

The current L3 GPR data processing (matlab code) takes a 256-point IFFT of the frequency-domain data (140-point data for mini-H and 70-point data for PSS-14). The frequency domain data provided to the IFFT is positive frequencies only, while the IFFT expects one full cycle of positive and negative frequencies (from 0 to 2π). Providing only positive frequencies is not necessarily detrimental to the processing, provided that it is done correctly. In fact, a theoretical construct, analytic signals, provides a mechanism to reduce the computational burden for transforming a purely real signal, such as the range-domain GPR signal, by working only with the positive half of the frequency-domain data. In order for analytic signals to be properly implemented, the frequency domain data provided to the IFFT must 1) be purely real at 0 and π, and 2) be equal to 0 for sample points greater than π. In addition, to maintain constant power in the signal, the magnitude of the frequency-domain spectrum must be doubled. The relationship between the original spectrum and the corresponding analytic signal spectrum is shown in Figure 3 for a synthetic signal composed of two sinusoids. Note that in the analytic spectrum, the positive frequencies (left half of the spectrum) have twice the magnitude of the original spectrum and the negative frequencies (right half of the spectrum) are equal to 0. The real part of the IFFT of the analytic spectrum is identically equal to the IFFT of the original spectrum.

In the case of the mini-H data, a 256-point IFFT is taken of the 140-point frequency spectrum. As shown in Figure 4, this closely approximates an analytic signal input to the IFFT, but there are some notable differences, namely 1) the input is not purely real at 0 and π, and 2) the input is not equal to 0 for frequency samples greater than π (negative frequencies). As a result of these discrepancies between an analytic spectrum and the spectrum provided to the IFFT, the range-domain signal resulting from the transform is not exactly equal to the true IFFT of the frequency-domain spectrum. Since it is quite similar to an analytic signal, however, the real part of the IFFT computed by the current implementation is quite close to the properly computed IFFT, though scaled by 0.5 since the magnitude has not been doubled to maintain constant power in the signal. If, instead, the mini-H data were augmented to create a true analytic signal by 1) doubling the magnitude of the frequency-domain data, 2) pre-pending a single purely-real sample at 0 (we chose a value of 0 for this sample), 3) appending a single purely-real sample at π (we chose a value of 0 for this sample), and 4) appending 140 zeros for the negative frequencies prior to taking the real part of a 282-point IFFT, then the result would be the true range-domain signal corresponding to the frequency-domain data. Alternatively, the complex conjugate of the original frequency-domain data could be constructed (with the addition of purely-real values at 0 and π), and the 282-point IFFT of this signal would also be the true range-domain signal corresponding to the frequency-domain data. Example range-domain signals are shown in Figure 5. The red and yellow curves correspond to properly computed IFFTs of the frequency-domain data via an analytic signal representation (red) and complex conjugate construction (yellow). The resulting range-domain signals are identical because the two methods are equivalent. The blue curve corresponds to the current IFFT implementation (shifted 2 samples to the right in order to align the ground bounce with the other signals), and the green curve shows the result that would be obtained by taking a 282-point IFFT without fully considering the requirements for an analytic signal. Note that although the current implementation is not a precisely accurate implementation of analytic signal representations, it is close enough that the end result (blue curve) appears to be a slightly compressed version of the true range-domain signal (red and yellow curves).

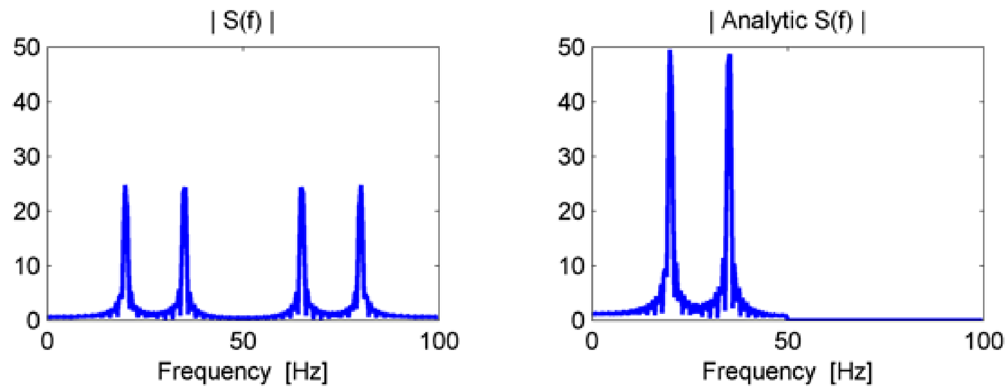

Figure 3. Example frequency-domain spectrum of a synthetic signal composed of two sinusoids (left) and the corresponding analytic signal spectrum(right).

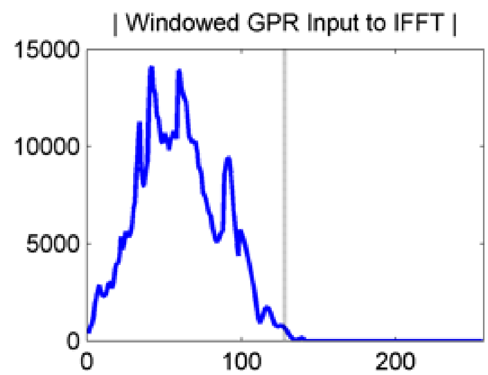

Figure 4. Mini-H frequency-domain data provided to IFFT.

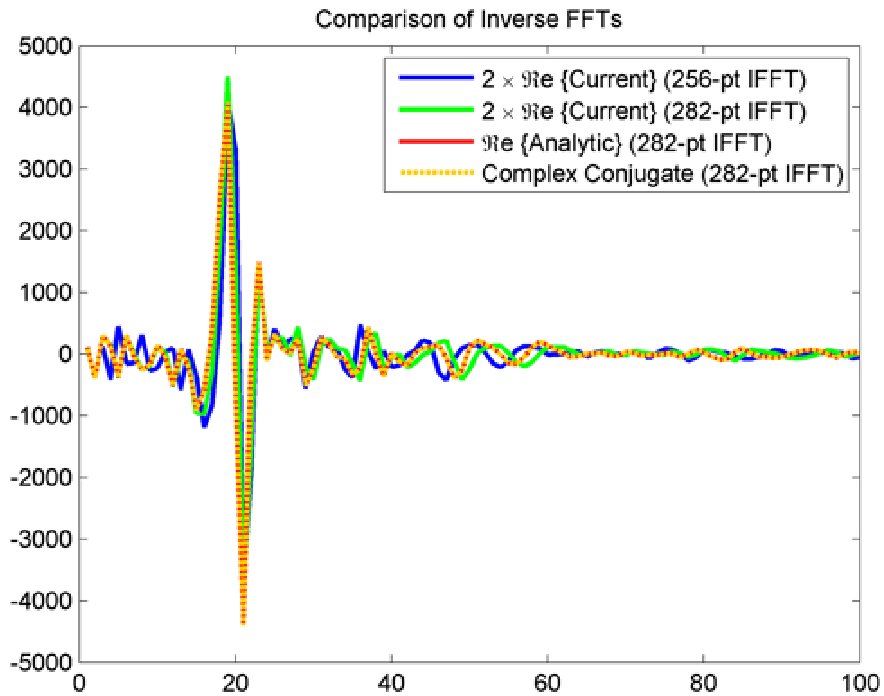

Figure 5. Inverse FFTs of Mini-H frequency-domain data provided to IFFT. Current implementation using the real part of a 256-point IFFT of the frequency-domain data (scaled by 2 to maintain constant power, and shifted 2 samples to the right to align the ground bounce with the other signals) (blue). The real part of a 282-point IFFT of the frequency-domain data (scaled by 2 to maintain constant power) (green). The real part of the 282-point IFFT of a properly constructed analytic signal representation (red). The 282-point IFFT of a properly constructed complex-conjugate frequency-domain data signal (yellow).

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